

University of Groningen

## Modeling crime scenarios in a Bayesian Network

Vlek, Charlotte; Prakken, Henry; Renooij, Silja; Verheij, Bart

*Published in:*

Proceedings of the 14th International Conference on Artificial Intelligence and Law (ICAIL 2013)

**IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.**

*Document Version*

Early version, also known as pre-print

*Publication date:*

2013

[Link to publication in University of Groningen/UMCG research database](#)

*Citation for published version (APA):*

Vlek, C., Prakken, H., Renooij, S., & Verheij, B. (2013). Modeling crime scenarios in a Bayesian Network. In *Proceedings of the 14th International Conference on Artificial Intelligence and Law (ICAIL 2013)* (pp. 150-159). ACM Press. <http://www.ai.rug.nl/~verheij/publications/icail2013.htm>

### Copyright

Other than for strictly personal use, it is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license (like Creative Commons).

The publication may also be distributed here under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license. More information can be found on the University of Groningen website: <https://www.rug.nl/library/open-access/self-archiving-pure/taverne-amendment>.

### Take-down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

*Downloaded from the University of Groningen/UMCG research database (Pure): <http://www.rug.nl/research/portal>. For technical reasons the number of authors shown on this cover page is limited to 10 maximum.*

# Modeling Crime Scenarios in a Bayesian Network

Charlotte Vlek  
Institute of Artificial  
Intelligence  
University of Groningen  
c.s.vlek@rug.nl

Henry Prakken  
Department of Information and  
Computing Sciences  
Utrecht University  
and Faculty of Law  
University of Groningen  
h.prakken@uu.nl

Silja Renooij  
Department of Information and  
Computing Sciences  
Utrecht University  
s.renooij@uu.nl

Bart Verheij  
Institute of Artificial  
Intelligence  
University of Groningen  
b.verheij@ai.rug.nl

## ABSTRACT

Legal cases involve reasoning with evidence and with the development of a software support tool in mind, a formal foundation for evidential reasoning is required. Three approaches to evidential reasoning have been prominent in the literature: argumentation, narrative and probabilistic reasoning. In this paper a combination of the latter two is proposed.

In recent research on Bayesian networks applied to legal cases, a number of legal idioms have been developed as recurring structures in legal Bayesian networks. A Bayesian network quantifies how various variables in a case interact. In the narrative approach, scenarios provide a context for the evidence in a case. A method that integrates the quantitative, numerical techniques of Bayesian networks with the qualitative, holistic approach of scenarios is lacking.

In this paper, a method is proposed for modeling several scenarios in a single Bayesian network. The method is tested by doing a case study. Two new idioms are introduced: the scenario idiom and the merged scenarios idiom. The resulting network is meant to assist a judge or jury, helping to maintain a good overview of the interactions between relevant variables in a case and preventing tunnel vision by comparing various scenarios.

## 1. INTRODUCTION

Problematic legal cases have recently called for a scientifically founded method of dealing with the qualitative and quantitative roles of evidence in a case. By developing a formal method, we aim to lay the foundations for the development of a software support tool that can deal with evidential reasoning in legal cases. Such a tool is meant to be

used by a judge or juror, in collaboration with various experts who can provide information about the details. This will hopefully improve the communication between judges or jurors and experts.

Three approaches to evidential reasoning have been leading in the literature: argumentation, narrative and probabilistic reasoning [16, 25]. In a previous project [6, 5, 7, 8], the combination of narrative and argumentation for legal cases was studied, which led to the development of a hybrid theory combining the two approaches. In this paper we study the combination of narrative with a probabilistic approach, proposing a systematic method for modeling legal scenarios in a Bayesian network.

A scenario is a coherent presentation of a sequence of events [6] and captures the greater picture of what may have happened at a crime scene. It provides a context for the available evidence. Judges and jurors are used to thinking in terms of stories or scenarios, and use scenarios to organize the evidence [20]. Based on these scenarios, we aim to systematically construct a Bayesian network modeling the case.

Bayesian networks have been studied as a tool for probabilistic reasoning about legal cases [14, 17, 18, 24]. The application of Bayesian methods in court is currently the subject of debate, so more research is needed [10]. On one hand, in the UK the Court of Appeal ruled in 2010 that Bayes' theorem should not be used in evaluating evidence, except for DNA and 'possibly other areas where there is a firm statistical base' [1]. On the other hand, in the Netherlands the use of Bayesian thinking has recently been advocated by a member of the Supreme Court together with the Netherlands Forensic Institute (Nederlands Forensisch Instituut, NFI) [3, 4, 2].

A Bayesian network is a representation of a joint probability distribution over a collection of relevant variables. The graphical structure shows the (in)dependencies between the variables in a case. In the application of Bayesian networks to legal cases, the graph usually contains one or more nodes with hypotheses (such as 'suspect X is guilty'), nodes with evidence (such as 'a fingerprint match was found with suspect X') and possibly some intermediate nodes (such as 'suspect X was at the crime scene' or 'suspect X left a fin-

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from [Permissions@acm.org](mailto:Permissions@acm.org).

ICAIL '13, June 10 - 14 2013, Rome, Italy

Copyright 2013 ACM 978-1-4503-2080-1/13/06 ...\$15.00.

gerprint’). Arrows between nodes are drawn whenever there is some probabilistic dependency between the variables (for example, between ‘suspect X left a fingerprint’ and ‘a fingerprint match was found with suspect X’).

When constructing a Bayesian network for a legal case, it is not always clear which variables are relevant to the case. This contrasts with, for example, the medical field where for most patients coming in with a set of symptoms, a doctor knows in advance which tests will be relevant to perform, what their possible outcomes are, and how these outcomes are related to various diagnoses. In other words, in many cases a previously developed Bayesian network can be used, and diagnosing a patient consists of instantiating the nodes in the network with the outcomes of the tests.

As opposed to this relatively closed world of medical testing, the legal field is often an open world where unpredictable relevant circumstances might turn up. For example, the fact that a bus did not run on schedule on the morning of the crime may turn out to be important when the suspect’s alibi includes taking this bus to work that day. As yet, there is for domains like the legal field no systematic approach to decide which variables should be included in a Bayesian network for a case.

In this paper, we propose such a systematic method, modeling crime scenarios in a Bayesian network. We argue that scenarios provide an advantage for determining which variables are relevant, because of their holistic point of view. A scenario makes sense of the collection of variables in a case by putting them in a coherent whole [22]. The local coherence of a scenario connects states and events that are directly related. And there is a global coherence between all states and events in one scenario, simply because together they form one scenario.

Currently, our focus lies on constructing the graphical structure of a Bayesian network. The resulting network is explicitly not intended to make a decision, but rather to advise and assist a judge or jury in making the decision. Moreover, however accurate the model, making a decision about one individual remains a delicate matter. One can always argue that this particular suspect was an exception or an outlier with respect to the probabilities. Therefore, the model should be used to *compare* how probable various scenarios are given the evidence, rather than to calculate an absolute probability.

Using the resulting Bayesian network, a judge or jury can evaluate the scenarios in a case. Studying the graphical structure, he or she can gain much insight into how the variables are connected. Furthermore, considering multiple scenarios prevents tunnel vision.

Our method builds upon work by Hepler, Dawid and Leucari [14] and Fenton, Neil and Lagnado [13, 11, 12, 18], who proposed to approach the construction of Bayesian networks via smaller substructures. The latter authors developed a list of *legal idioms*, substructures that often occur in the application of Bayesian networks to legal cases. We extend their list with a *scenario idiom* and a *merged scenarios idiom*. Furthermore, we add to their work a procedure for the global structure of a full Bayesian network, employing the local structures of the idioms.

In this paper, we follow the method of first developing a design method, and then testing this method by means of a case study. The design method for modeling crime scenarios in a Bayesian network is presented in Section 3, illustrated

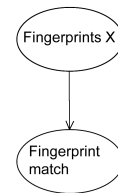


Figure 1: Example of a Bayesian network

Fingerprints X = yes	Fingerprints X = no
0.2	0.8

Table 1: The prior probability  $P(\text{Fingerprints } X)$

	FP X = yes	FP X = no
Fingerprint match = yes	0.9	0.01
Fingerprint match = no	0.1	0.99

Table 2: CPT for  $P(\text{Fingerprint match} | \text{Fingerprints } X \text{ on windowsill})$

with brief examples. The case study is performed in Section 4. In Section 5 the properties of the proposed method are discussed. The paper concludes with a section on related work (Section 6) and a conclusion.

## 2. PRELIMINARIES

A Bayesian network is a representation of a joint probability distribution (JPD) [15]. A JPD is a function that, for all combinations of values of variables in the domain, gives the probability that they occur. The graphical structure of a Bayesian network is a way to represent the independencies between variables in a JPD: when there is no arrow between two nodes in the Bayesian network, then the corresponding variables are independent given all other variables in the domain. When there is an arrow, this means that there is some correlation between two variables. The arrows are commonly directed from cause to effect [24], but represent correlation rather than causality [9].

Each node in a Bayesian network has a conditional probability table (CPT). Such an CPT gives the (conditional) probability of the different values of a variable, conditioned on the different value combinations for all its direct predecessors. Figure 1 shows a Bayesian network, with probability tables as in Tables 1 and 2. In combination with the graph representing (in)dependencies, these probability tables define a full joint probability distribution.

After constructing the network, variables can be instantiated whenever their value is observed in practice. Inference in the network now results in updated posterior probabilities given all observed values in the network. Depending on the types of connections, the (in)dependencies between variables may change as a result of instantiating variables. When two variables are connected through a chain that does not contain so-called *head-to-head nodes* (a variable with two incoming arrows), the chain is said to be *active* if and only if none of the variables on the chain is instantiated. A chain that includes a head-to-head node is inactive if neither the

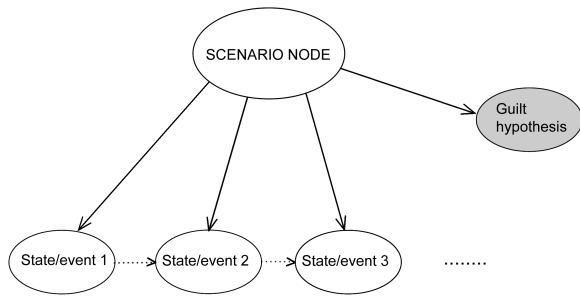


Figure 2: The scenario idiom

head-to-head node, nor any of its descendants, is instantiated. Two nodes are said to be d-connected if they are connected by a least one active chain; otherwise they are d-separated [15].

A Bayesian network is a compact representation of a joint probability distribution over all relevant variables. Constructing a Bayesian network implies that there is knowledge of all these probabilities, but in practice this is usually not the case. Eliciting the numbers is a known issue in Bayesian network modeling. In some cases the probabilities are straightforward (for example, numbers concerning the accuracy of a DNA-test are usually available), while in other cases they are not. Several methods are available for guiding an expert to determine such numbers (see [21]).

### 3. DESIGN METHOD

In this section the design method for modeling crime scenarios in a Bayesian network is described. The goal of the method is to model all scenarios for a legal case in one Bayesian network, connecting them to the available evidence. In Section 3.1 the new idioms are introduced and in Section 3.2 the procedure of the design method is presented.

#### 3.1 The scenario idiom and the merged scenarios idiom

Consider the following example of a scenario:

Suspect X had a fight with the victim. A knife was lying on the kitchen counter. The victim said something insulting, so X took the knife and stabbed the victim.

It describes a typical situation of a violent fight: the suspect snapped and took up the knife that happened to be lying around. This sequence of states and events is a coherent scenario that follows a typical crime pattern. The coherence will be captured in the scenario idiom by connecting all states and events in the scenario to one scenario node. Furthermore, there are some obvious connections in the scenario, such as ‘the victim said something insulting, so X took the knife...’ which describes a motive. Such connections will be modeled as arrows between states or events in the story.

Figure 2 shows the structure of the scenario idiom. It consists of a scenario node which is connected to all states and events in the scenario. The dotted arrows suggest that there can be connections between states and events within the scenario, including multiple dependencies (not shown).

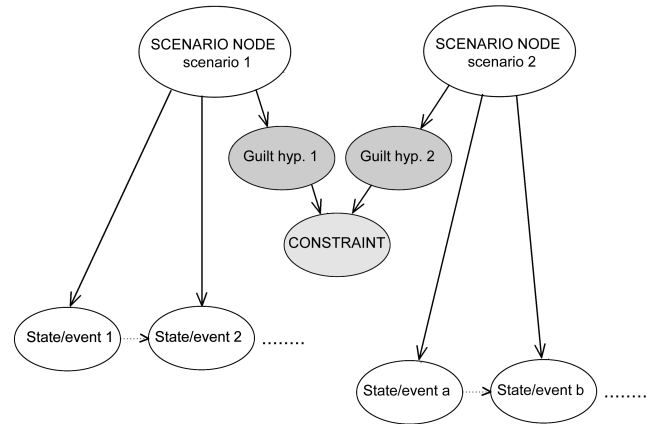


Figure 3: The merged scenarios idiom

All nodes in the structure are binary, with values true and false.

The scenario node is connected to a guilt hypothesis node. A guilt hypothesis states that some suspect is guilty or innocent of some crime. This is modeled as a separate node because this is ultimately what a judge or jury wants to decide upon. As the scenario node becomes more probable, the guilt hypothesis node will also become more probable.

The scenario above supports the hypothesis that X is guilty of manslaughter. Other scenarios can support the hypothesis that X is guilty of murder, or that another person Y is guilty of manslaughter. There can be scenarios without a guilt hypothesis; a scenario in which the victim accidentally fell on the knife does not support anyone committing any crime. In that case, the guilt hypothesis node is left out of the scenario idiom. Note that the victim falling on the knife does not *disprove* any guilt hypothesis either; it just supplies an alternative explanation.

After each scenario is put into the form of a scenario idiom, these are combined in one Bayesian network using the merged scenarios idiom. This idiom puts a constraint on the guilt hypotheses of the previously constructed scenario idioms, see Figure 3. The constraint makes sure that mutually exclusive guilt hypotheses cannot occur simultaneously.

#### 3.2 The design method in four steps

Given a legal case, the design of a Bayesian network consists of four steps.

**Step 1** is to collect all relevant scenarios, and decide which guilt hypotheses they support. It is important that these hypotheses are formulated such that they are either equal, or mutually exclusive (this will be important for the merged scenarios idiom). It is possible that a scenario does not support any guilt hypothesis; see the case study below.

In **step 2** the scenario idiom is filled in for each scenario. The scenario idiom can be constructed from a scenario by following these three steps:

- 2a Include a binary node with values true and false for each state/event in the scenario (for convenience, the order in which the states and events were presented in the scenario can be kept as the ordering of the nodes from left to right). Whenever events or states are de-

	Scenario node = y	Scenario node = n
Event = y	1	$x$
Event = n	0	$1-x$

**Table 3: CPT for an event node only connected to the scenario node**

pendent on each other (see [19] for dependencies between variables), draw an arrow between the corresponding nodes. Check that unconnected nodes are really independent, since in a Bayesian network the absence of an arrow always implies independence.

- 2b For each scenario distinguished in step 1, include a scenario node with values true and false, and draw an arrow from the scenario node to all state and event nodes in that scenario. The probability table for an event node expresses how strongly an event is connected to other states and events to which it is connected. As for the connection with the scenario node, when the scenario node is true, the event is true with probability 1. When the scenario node is false, the numbers express how probable the event is without the scenario being true. A probability table for an event node only connected to the scenario node is shown in Table 3.

The prior probability for the scenario node expresses the plausibility of the scenario: how probable the scenario is when no evidence was taken into account. The plausibility of a scenario is said to depend on how well a scenario can be understood using common sense knowledge (see [6, 26]). Therefore, the corresponding prior probability can very well be a quite subjective estimation of a judge or jury, supported by his or her common sense knowledge.

- 2c Include a node with values true and false for the guilt hypothesis that each scenario supports. Draw an arrow from the scenario node to the guilt hypothesis. Later on, it may be that multiple scenario nodes are connected to the same guilt hypothesis (they draw the same conclusion on a suspect’s guilt, but via a different account of what happened). In that case, the probability table can be more intricate. At this stage we can set the probability table to imply that the guilt hypothesis is true exactly when the scenario node is true.

For the example scenario of the violent fight, all events such as ‘the victim said something insulting’ or states such as ‘a knife was lying around on the kitchen counter’ will be modeled as a node in the structure. Connections within the scenario will be drawn when they are present, such as, for example, between ‘the victim said something insulting’ and ‘X took the knife’. The coherence we previously mentioned is represented in the fact that they are all connected to one scenario node.

The probability tables will incorporate how probable an event is without the context of the scenario. The lower this probability, the more the likelihood depends on the coherence of the scenario. This global coherence will be of importance when the network is used for the evaluation of a case and evidence nodes are instantiated. Then all states and events in one scenario become more probable when evidence for single events or states are added (see Section 5).

	Guilt hyp.1 = y		Guilt hyp.1 = n	
	GH2 = y	GH2 = n	GH2 = y	GH2 = n
allowed	0	1	1	1
not allowed	1	0	0	0

**Table 4: CPT for the constraint node**

**Step 3** is to merge all scenario idioms with the merged scenarios idiom (see Figure 3), which puts a constraint on the guilt hypotheses. When guilt hypothesis nodes connected to different scenario nodes express equal hypotheses, they are replaced by one node connected to both scenario nodes. The probability table for the one new node expresses that the guilt hypothesis is true when either one of the scenarios to which it is connected is true<sup>1</sup>. By construction (see step 1), the remaining guilt hypotheses are mutually exclusive. The constraint from the merged scenarios idiom is then only connected to mutually exclusive hypotheses, as was intended.

The constraint node (see also [13]) of the merged scenarios idiom has values **allowed** and **not allowed** and is always instantiated to have the value **allowed**. This forces the Bayesian network to behave as desired. In the probability table, the probability that the constraint is allowed is 0 when two mutually exclusive hypotheses are true simultaneously, and 1 in all other cases<sup>2</sup>, see Table 4.

After merging all scenarios into one Bayesian network, there can be additional dependencies that have not yet been modeled as an arrow. These additional dependencies can occur between state or event nodes in different scenario idioms. We assume that the scenarios are self-contained in the sense that when a state or event is influential for a scenario, then it is already in the scenario. If this is not the case and additional dependencies with events from other scenarios turn up, then the scenarios should be reformulated to contain all relevant events. Then, the only dependencies that can occur between two scenario idioms are two nodes that describe equal states or events, or two nodes that describe states or events inconsistent with each other.

Therefore, when using the merged scenarios idiom, the following situations need to be taken care of:

3a nodes describing equal states, events or evidence;

3b nodes describing conflicting states, events or evidence;

When nodes describing the same state, event or evidence (item 3a) occur in different scenarios, they are replaced by one node for that state, event or evidence. Any nodes that were connected to the original nodes will now be connected to the one resulting node. For example, an alternative scenario to the violent fight above is that suspect X intended to kill the victim all along, and therefore brought the knife himself. In this scenario, the event that X stabbed the victim is still present, but the rest of the scenario is different.

<sup>1</sup>Alternatively, the probability table can be adapted to express that the probability of guilt should increase more when both scenarios are the case.

<sup>2</sup>In this construction, the constraint node only makes sure that no two mutually exclusive hypotheses occur together. When the hypotheses are also exhaustive so at least one of them should occur, then the constraint node could have probability 0 for the value allowed when none of the hypotheses are the case.

In the resulting Bayesian network, there will be only one node for the event ‘X stabbed the victim’, that is connected to both scenario nodes. Two different scenarios may contain states or events that cannot possibly occur simultaneously (item 3b). In that case, a constraint is put on these states or events with a constraint node as used on the guilt hypotheses.

**Step 4** is the final step and consists of adding all relevant evidential nodes to the structure. For each piece of evidence that has been found in the investigative process, a binary evidential node will be included. Furthermore, when a specific piece of evidence can be expected as a result from a scenario, a binary evidential node is included for this evidence, even when it has not yet been found.

Each evidential node will be connected to the event or state node in the scenario it supports. Note that one piece of evidence may support multiple states or events in different scenarios. Intermediate nodes may be required to model the interpretation of the evidence: suppose a witness testified that he heard suspect X fight with the victim. The interpretation of this piece of evidence is that the witness did in fact hear the two fight, which we can connect to the event ‘Suspect X had a fight with the victim’. However, it is very well possible that the witness lied, meaning that the interpretation is incorrect. We model this in the structure using Fenton, Neil and Lagnado’s ‘evidence accuracy idiom’ [13]. Finally, there may be dependencies between pieces of evidence, which can be represented in the Bayesian network using Fenton, Neil and Lagnado’s idioms for dependency between evidence.

To summarize, our design method consists of the following four steps:

1. Formulate all scenarios and decide which hypotheses they support. Make sure that hypotheses are either exactly the same, or mutually exclusive.
2. Represent each scenario in a scenario idiom.
3. Merge multiple scenarios using the merged scenarios idiom.
4. Extend the structure with relevant evidence.

The resulting graph will be connected, since different scenarios either point to the same guilt hypothesis, or to mutually exclusive hypotheses that are connected via a constraint node.

## 4. CASE STUDY

In this section, we test our design method to an actual case. We model a Dutch case from [www.rechtspraak.nl](http://www.rechtspraak.nl). The case (registered as JLN BO 4007) concerns a burglary in which a number of items were stolen.

A window was broken and fingerprints of suspect X were found at the window. X explained these fingerprints with an alibi saying that he climbed on that window a few days earlier because he heard someone calling his name while he walked by, drunk. However, the windows were cleaned just before the burglary, which would almost certainly have removed earlier fingerprints.

The stolen items were found with another suspect, call him Y. An earlier conviction supposedly showed that X and Y had worked together in the past, which led to the conviction of X as an accessory. However, when the case was

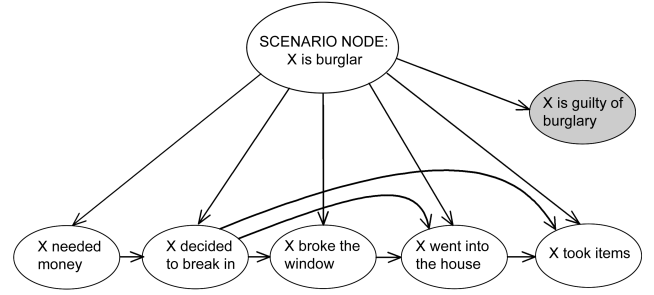


Figure 4: The scenario idiom for the first scenario

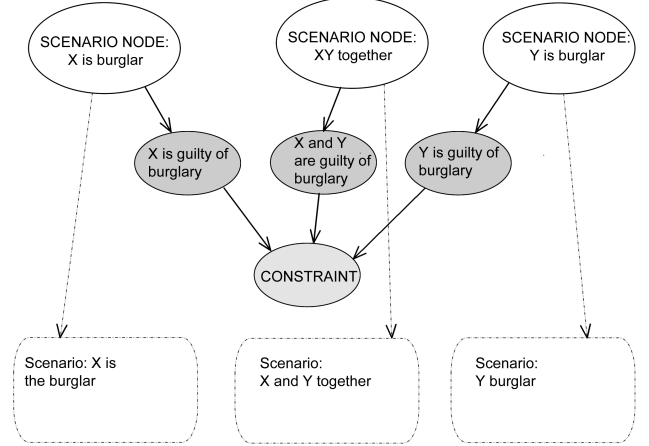


Figure 5: A constraint on mutually exclusive hypotheses. The collection of states and events in each scenario is shown as a dotted box for simplicity.

reopened no documents on an earlier conviction could be found.

In the sections below, we will show how our design method from Section 3 can be used to construct a Bayesian network for the case. The structure of the full Bayesian network can be found in Figure 9.

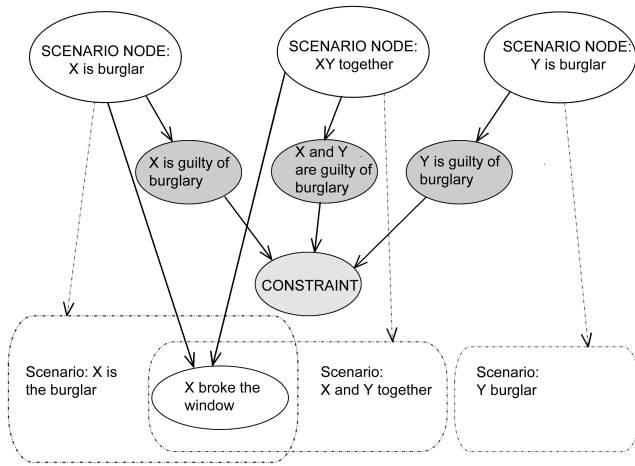
### 4.1 Step 1: the scenarios

The first step in our design method is to formulate all relevant scenarios, and which hypotheses they support. In this case, there will be scenarios describing that X was the burglar, that X and Y worked together or that Y was the burglar. There is also a scenario describing how X climbed the window. The scenarios below are based on our interpretation of the case.

- Scenario 1, supporting the hypothesis that X is guilty of burglary and worked alone:

X needed money, so X decided to break in.  
X broke the window of the house, went in  
and took some items from the house.

- Scenario 2, supporting the hypothesis that Y is guilty of burglary and worked alone:



**Figure 6: The same event in two scenarios. Each scenario is represented as a dotted box for simplicity.**

Y needed money, so Y decided to break in. Y broke the window of the house, went in and took some items from the house.

- Scenario 3, supporting the hypothesis that X and Y are guilty of the burglary together:

Y needed money. Y decided to break in. X and Y had previously committed a crime together, so Y asked X to help him with a burglary. X broke the window of the house, X and Y went in and Y took some items from the house.

- Scenario 4, supporting no hypothesis, but supplying an alternate explanation for the fingerprint evidence:

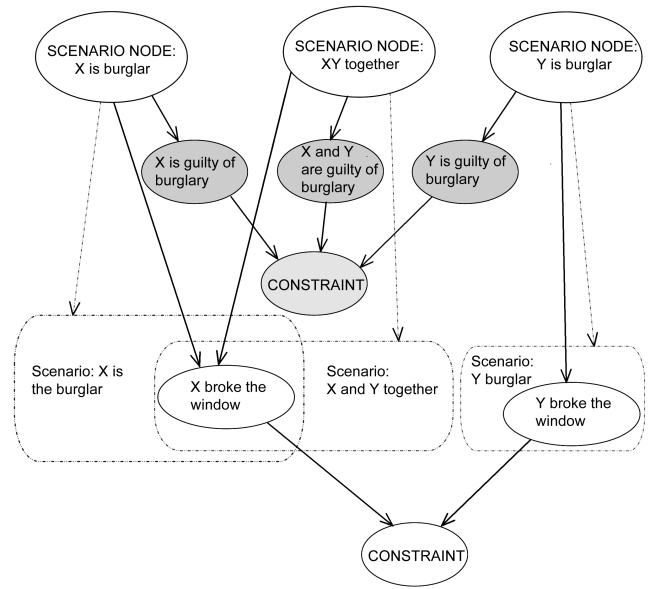
X was drunk on a night a few days before the burglary. X walked by the house and thought he heard someone calling his name. Therefore, X climbed on the window.

Note that the guilt hypotheses are mutually exclusive but the scenarios are not. In particular, the fourth scenario does not support any guilt hypothesis, nor does it support the opposite (X is not guilty of burglary): it merely provides an alternate explanation for the fingerprints on the window. In the resulting Bayesian network, a higher probability for this fourth scenario will indirectly lead to a slightly lower probability for the scenario in which X is the burglar.

## 4.2 Step 2: the scenario idioms

In the second step of our design method, each scenario is worked out with the scenario idiom. Figure 4 shows the scenario idiom for the first scenario, where X was the sole burglar.

The probability tables for all states and events in the scenario express that they follow logically from the scenario node. When the scenario node is not true, the numbers express how probable the state or event is without the context of the scenario, given the value of the other states and events to which it is connected. Eliciting these numbers is not at



**Figure 7: Conflicting events in two scenarios. Each scenario is represented as a dotted box for simplicity.**

all a trivial task, and it is often a subjective matter (see [21]). As an illustration we show how some numbers can be picked. When the scenario node has value true, we have  $P(X \text{ went into the house}=\text{yes} | X \text{ broke the window}=\text{yes}, \text{SCENARIO NODE}=\text{yes}) = 1$ . The probability that X went into the house without the context of this particular scenario is quite low, since people do not go in to other people's houses for no reason. Therefore, we set  $P(X \text{ went into the house}=\text{yes} | X \text{ broke the window}=\text{no}, \text{SCENARIO NODE}=\text{no}) = 0.05$ . The other probability tables should be filled in similarly.

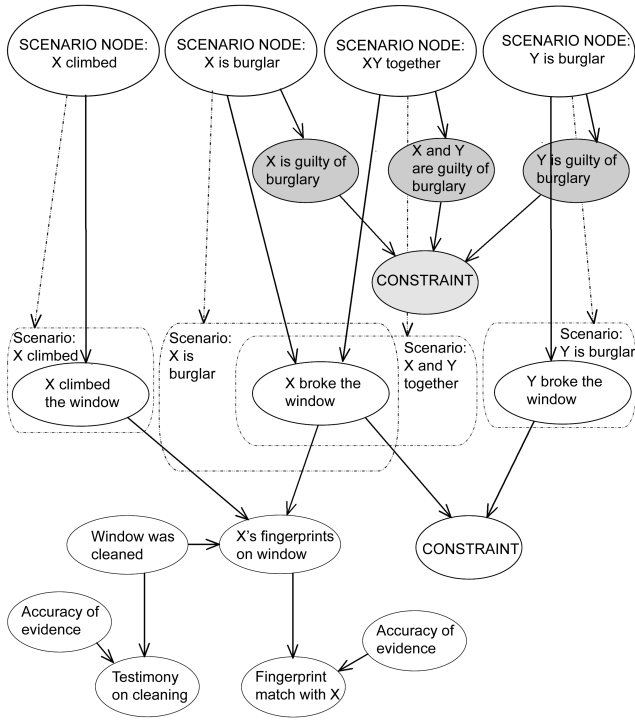
The guilt hypothesis follows with probability 1 from the scenario. The prior probability of the scenario node expresses how plausible the general pattern of this scenario is, without taking into account any evidence yet. For this example, we choose a prior probability of  $P(\text{SCENARIO NODE} = \text{yes}) = 0.01$ . Similarly, the scenario idioms for the other scenarios are constructed.

## 4.3 Step 3: merging the scenarios

All scenarios are merged with the merged scenarios idiom. The first three scenarios support three hypotheses that are all mutually exclusive: X is guilty, Y is guilty and X and Y are both guilty. Note that these are really mutually exclusive. In our example case, no two scenarios support the same hypothesis. When combining the scenarios with the merged scenarios idiom, a constraint node is added as shown in Figure 5. In this image, each scenario with all its states and events is shown schematically as a dotted box, for simplicity.

The constraint node has values **allowed** and **not allowed**, and is always instantiated to **allowed**. The probability that the value is allowed is 0 when two or more hypotheses are true simultaneously, and 1 otherwise.

Now overlapping and conflicting states or events (items 3a and 3b from Section 3) need to be taken care of. The event



**Figure 8: Evidence for two scenarios. Each scenario is represented as a dotted box for simplicity.**

that X broke the window occurs both in the scenario where X is the sole burglar and in the scenario in which X and Y worked together (3a). Therefore, when putting the two scenarios together this is replaced by one node, as shown in Figure 6. Similarly, the event that Y took items from the house is the same in the scenario of X and Y working together and in scenario in which Y is the burglar. These nodes also become one node in the structure.

The event that X broke the window conflicts with the event that Y broke the window (3b). Therefore, a constraint node is added: see Figure 7. Like before, the constraint node has values **allowed** and **not allowed**, and is always instantiated on **allowed**. The probability that the value is **allowed** is 0 when the two events are both true, and 1 otherwise.

#### 4.4 Step 4: adding the evidence

Finally, evidential nodes are added to the structure. As an example, we show how the evidence of X's fingerprints on the window can be added, see Figure 8. Via an intermediate node describing that X's fingerprints were on the window, it supports both X breaking the window and the event that X climbed the window. Recall that for the fourth scenario there was also a witness testimony to state that the window was recently cleaned, which would almost surely have removed earlier fingerprints from X climbing the window. We combine this evidence to find a structure as shown in Figure 8, using the evidence accuracy idiom from [13].

Similarly, other evidence can be added to the network. Figure 9 shows a Bayesian network structure for this case.

## 5. FEATURES OF THE DESIGN METHOD

The design method as described in this paper models crime scenarios for a legal case in a Bayesian network. In this section, some features of the method will be discussed.

The proposed design method has currently been presented as producing a static representation of all the variables in a case. Nonetheless, the method can be used to produce new models at different moments in time, for example during an investigative process.

The network can be adapted and extended as new evidence and scenarios turn up. In fact, scenarios can help in the finding of new evidence in the form of so-called *story consequences* [6], one source of the critical questions that can drive further investigation [8]. For example, when one scenario involves the suspect driving off in a red car, witnesses can be sought to testify whether they saw a red car at the appropriate time. With these story consequences, scenarios can add relevant variables to the domain that may otherwise have been overlooked. Had there only been variables directly concerning the crime or the known evidence, then the red car would not have been included.

With the scenario idiom, the coherence of a scenario is modeled in the Bayesian network. A scenario is said to be a coherent sequence of states and events (see [6, 20]). The coherence of a scenario reflects that our belief in the entire scenario strengthens, as we know more about the circumstances. For example, when we find that suspect X went into the house through the window, we tend to believe more in the entire scenario and all the events it consists of: by learning that X went into the house through the window, we believe he probably also took some items from the house.

The scenario idiom captures this coherence by connecting all states and events in one scenario to a scenario node, resulting in the probabilities in the Bayesian network to behave as desired. This is because by construction, all state and event nodes in the scenario are d-connected: between any two state or event nodes there is a path through which information can be transmitted [15]. To see this, consider the scenario idiom from Figure 4. There cannot be direct evidence for the scenario node, leaving it uninstantiated. Since the connections from the scenario node to the state and event nodes diverge (the arrows do not meet head-to-head in the scenario node), information about one state or event is relevant for other states and events in the scenario<sup>3</sup>.

Therefore, when evidence for one of the states or events of a scenario is instantiated in the network, this has an effect on the probability of all states or events in the scenario and the probability of the guilt hypothesis. We say that evidential support is transferred via the scenario node.

A less desirable feature of the scenario idiom is that it requires probabilities for some quite abstract connections to be made explicit, in order to model the coherence of a scenario. The issue of eliciting the numbers in a Bayesian network is known, but with the scenario idiom, some particularly abstract connections were introduced. The arrows from the scenario node to the state or event nodes were said to express how probable a state or event is without the context of the scenario (see Section 3). It is to be investigated whether existing elicitation techniques produce useful numbers for

<sup>3</sup>Note that for two d-connected nodes, information about one node is not necessarily relevant for the other; there may still be an independence due to the numbers in the probability tables.





these connections.

A positive feature of the scenario idiom is that it can model the plausibility of a scenario by means of the prior probabilities for the scenario node. For example, when a scenario describes a burglary but fails to explain how the burglar got into the house, it will not be perceived as a proper explanation of what has happened. When this scenario is modeled in a Bayesian network with our design method, the low plausibility will be reflected in a low prior probability for the value true of the scenario node.

Note that a very implausible scenario can become probable when enough evidence is available. For example, when a burglar is caught red-handed by the police, it is less important to know how he got in. The Bayesian network behaves the same: a low prior probability can result in a high posterior probability when enough evidence is added.

With the merged scenarios idiom, multiple scenario can be modeled in one Bayesian network. These various scenarios can be compared in the network and help to prevent tunnel vision among judges and jurors.

Including multiple scenarios in one Bayesian network may lead to a very large network with many nodes (cf. also Figure 9). However, from a modeling perspective it is desirable to include all scenarios in one network as opposed to separate networks for each scenario. This is because the scenarios must be compared, and events and states from different scenarios will overlap. When working with separate networks, the maintenance of equal numbers in different models can be a cumbersome task, especially when the models frequently change in the investigative process.

To summarize, the main contribution of the proposed design method is that it uses crime scenarios as a basis for a Bayesian network. The advantage of using scenarios lies in the holistic perspective. Since a scenario considers what may have happened in a legal case as a whole, it can help to find more evidence, for example via story consequences.

With the scenario idiom, the coherence of a scenario is captured as well as its plausibility. However, the scenario idiom requires some abstract probabilities to be determined.

With the merged scenarios idiom, multiple scenarios can be modeled in one Bayesian network. This allows for a comparison between scenarios, evaluating which is most probable.

## 6. RELATED WORK

In recent work on Bayesian networks applied to legal cases, Hepler, Dawid and Leucari [14] proposed the idea of often recurring substructures in Bayesian networks. Fenton, Neil and Lagnado [13, 12, 18] elaborated on this idea by compiling a list of legal idioms: building blocks for the construction of a Bayesian network for a legal case. With their idioms, Fenton, Neil and Lagnado aimed to systematise the construction of Bayesian networks for legal cases. Their approach is very helpful in finding the structure of the network on a local level. For example, with their evidence accuracy idiom one can quickly see that any piece of evidence should be connected to a node that describes the accuracy of evidence.

Our design method extends this local approach to the holistic perspective of scenarios. We have added two new idioms, the scenario idiom and the merged scenarios idiom. With a design method, we can systematically build Bayesian networks for legal cases based on scenarios.

Scenarios show which variables are relevant to the case and which are not. Research on the application of narrative to legal cases, such as [20, 26], stresses the importance of the coherence of a scenario. With the scenario idiom, we have incorporated the idea of global coherence into our models. Furthermore, we can compare various scenarios with the merged scenarios idiom. In our models, scenarios are compared as a whole and not just in terms of their elements.

Comparing multiple scenarios in one Bayesian network is relevant, since looking at various possible scenarios helps to prevent tunnel vision with judges and jurors. By incorporating multiple scenarios and thereby multiple hypotheses, our design method differs from Fenton, Neil and Lagnado's work, who focus on a single hypothesis in their method.

Our proposed design method combined two of the main approaches to legal reasoning: narrative and probabilistic reasoning. Recently, Keppens [17] studied the combination of Bayesian network with argumentation. Silano, Boer and Van Engers [23] studied narrative applied to law.

## 7. CONCLUSION

In this paper, we described a systematic method for modeling crime scenarios in a Bayesian network. We tested our method to a case study, where multiple scenarios were modeled in one single Bayesian network for the case. In the future our method should be further evaluated, for example by more extensive and realistic case studies.

The described method combines two well-known approaches for working with legal evidence: probabilistic reasoning in the form of Bayesian networks and narrative. Like any model, a Bayesian network is a limited representation of the real world and represents only as much as the designer includes. The holistic aspect of narrative helps to find all relevant variables in a case by considering all possible scenarios of what may have happened.

We have built upon work by Hepler, Dawid and Leucari [14] and Fenton, Neil and Lagnado [13], who proposed to use legal idioms in the construction of Bayesian networks. We have added a scenario idiom and a merged scenarios idiom for working with scenarios, and described a procedure for systematically constructing the whole Bayesian network for a case. We have thereby extended the systematization that the aforementioned authors initiated with the holistic perspective of scenarios.

Further research is needed on the specification of the probabilities in the probability tables. A number of methods exist [21] for determining the probabilities in a Bayesian network, but, given the known issue of finding useful numbers, it is worth investigating how well these methods are suited for the specific field of law.

Another interesting topic for further research is the coherence of scenarios. In the design method presented here, a novelty that we introduced was the use of the scenario idiom to capture the coherence of scenarios. One step further would be to develop a numeric measure for the degree of coherence of a scenario, by which scenarios can be compared.

## Acknowledgements

This work is part of the project "Designing and Understanding Forensic Bayesian Networks with Arguments and Scenarios" in the Forensic Science programme, financed by the Netherlands Organisation for Scientific Research (NWO).

## 8. REFERENCES

- [1] Regina v T, 2010. EWCA Crim 2439. Available on [www.bailii.org](http://www.bailii.org).
- [2] C. Berger and D. Aben. Bewijs en overtuiging: Een helder zicht op valkuilen. *Expertise en Recht*, 5/6:159 – 165, 2010.
- [3] C. Berger and D. Aben. Bewijs en overtuiging: Rationeel redeneren sinds Aristoteles. *Expertise en Recht*, 2:52 – 56, 2010.
- [4] C. Berger and D. Aben. Bewijs en overtuiging: Redeneren in de rechtszaal. *Expertise en Recht*, 3:86 – 90, 2010.
- [5] F. Bex. Analysing stories using schemes. In H. Kaptein, H. Prakken, and B. Verheij, editors, *Legal Evidence and Proof: Statistics, Stories, Logic*, pages 93 – 116. Ashgate Publishing, Aldershot, 2009.
- [6] F. Bex. *Arguments, Stories and Criminal Evidence, a Formal Hybrid Theory*. Springer, Dordrecht, 2011.
- [7] F. Bex, P. van Koppen, H. Prakken, and B. Verheij. A hybrid formal theory of arguments, stories and criminal evidence. *Artificial Intelligence and Law*, 18:123–152, 2010.
- [8] F. Bex and B. Verheij. Solving a murder case by asking critical questions: An approach to fact-finding in terms of argumentation and story schemes. *Argumentation*, 26:325–353, 2012.
- [9] A. Dawid. Beware of the DAG. In *Journal of Machine Learning Research: Workshop and Conference Proceedings*, volume 6, pages 59–86, 2009.
- [10] N. Fenton. Science and law: Improve statistics in court. *Nature*, 479:36–37, 2011.
- [11] N. Fenton and M. Neil. The “jury observation fallacy” and the use of Bayesian networks to present probabilistic legal arguments. *Mathematics Today*, 36(6):180 – 187, 2000.
- [12] N. Fenton and M. Neil. Avoiding probabilistic reasoning fallacies in legal practice using Bayesian networks. *Australian Journal of Legal Philosophy*, 36:114 – 151, 2011.
- [13] N. Fenton, M. Neil, and D. Lagnado. A general structure for legal arguments using Bayesian networks. *Cognitive Science*, 2012. doi: 10.1111/cogs.12004.
- [14] A. Hepler, A. Dawid, and V. Leucari. Object-oriented graphical representations of complex patterns of evidence. *Law, Probability & Risk*, 6:275–293, 2004.
- [15] F. Jensen and T. Nielsen. *Bayesian Networks and Decision Graphs*. Springer, New York, 2007.
- [16] H. Kaptein, H. Prakken, and B. Verheij. *Legal Evidence and Proof: Statistics, Stories, Logic*. Ashgate Publishing Company, Aldershot, 2009.
- [17] J. Keppens. On extracting arguments from Bayesian network representations of evidential reasoning. In K. Ashley and T. van Engers, editors, *The 13th International Conference on Artificial Intelligence and Law*, pages 141 – 150, New York, 2011. ACM.
- [18] D. Lagnado, N. Fenton, and M. Neil. Legal idioms: a framework for evidential reasoning. *Argument and Computation*, 2012.
- [19] J. Pearl. *Causality: Models, Reasoning and Inference*. Cambridge University Press, Cambridge, 2000.
- [20] N. Pennington and R. Hastie. Explaining the evidence: Tests of the story model for juror decision making. *Journal of Personality and Social Psychology*, 62(2):189 – 206, 1992.
- [21] S. Renooij. Probability elicitation for belief networks: Issues to consider. *The Knowledge Engineering Review*, 16(3):255 – 269, 2001.
- [22] R. Schank and R. Abelson. *Scripts, Plans, Goals and Understanding, An Inquiry into Human Knowledge Structures*. Lawrence Erlbaum, Hillsdale, 1977.
- [23] G. Sileno, A. Boer, and T. van Engers. Analysis of legal narratives: a conceptual framework. In *Legal Knowledge and Information Systems: JURIX 2012: the 25th Annual Conference*, pages 143–146, Amsterdam, 2012. IOS Press.
- [24] F. Taroni, C. Aitken, P. Garbolino, and A. Biedermann. *Bayesian Networks and Probabilistic Inference in Forensic Science*. Wiley, Chichester, 2006.
- [25] B. Verheij. Integrating argumentation, narrative and probability in legal evidence. In M. Finlayson, editor, *The Third Workshop on Computational Models of Narrative*, pages 176–177, 2012.
- [26] W. Wagenaar, P. van Koppen, and H. Crombag. *Anchored Narratives : the Psychology of Criminal Evidence*. Harvester Wheatsheaf, Hemel Hempstead, 1993.